



## Recommendation System: a Review of Trust Techniques

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Sarah Medjroud, Nassim Dennouni and Mourad Loukam

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# Recommendation System: a review of trust techniques

Sarah MEDJROUD  
Department of Computer Science  
Hassiba Ben Bouali University  
Chlef, Algeria  
s.medjroud@univ-chlef.dz

Nassim DENNOUNI  
LIA Laboratory, UHBC  
Higher School of Management  
Tlemcen, Algeria  
dennouninas@gmail.com

Mourad LOUKAM  
Department of Computer Science  
Hassiba Ben Bouali University  
Chlef, Algeria  
m.loukam@univ-chlef.dz

**Abstract**— This article highlights the growing application of artificial intelligence (AI) with a particular focus on the use of Implicit Trust-based Recommender Systems (ITRS). These systems leverage trust relationships between users inferred from their past actions such as reviews, check-ins, and clicks. In this article, two types of approaches are discussed. Firstly, explicit trust approaches which aim to improve the accuracy of recommendations by taking into account users' explicit declarations of trust. And secondly, implicit trust approaches are examined, which utilize implicit trust relationships among users inferred from their past behaviors. The overall analysis of these two approaches underscores the benefits of implicit trust in reducing the need for active user participation and alleviating the cold start problem of data sparsity. In conclusion, the article opens the way to new perspectives for item recommendation in the field of smart tourism using AI.

**Keywords**— Recommendation Systems, Explicit Trust, Implicit Trust, Cold Start, Data Sparsity.

## I. INTRODUCTION

Today, the utilization of artificial intelligence is on the rise for analyzing data obtained from the historical records of tourists on smart tourism websites and mobile apps. This analysis aims to extract information about their past locations, preferences, travel habits, and more.

AI-based recommendation systems analyze this data to identify items that are likely to interest a tourist at a given time. This may include restaurants, shops, tourist attractions, etc. Machine learning algorithms are often used to personalize recommendations based on the individual tastes and needs of each tourist.

Implicit Trust-based Recommender Systems (ITRS) focus on using implicit trust relationships among tourists to improve the accuracy of item recommendations. These trust relationships are inferred from tourists' past actions, such as item ratings, check-ins of visited places, clicks, etc. these ITRSs are often based on collaborative filtering approaches to compute preference similarities between tourists.

Implicit data, such as clicks, view times, downloads, are commonly used to infer implicit trust between users. These data are more abundant than explicit ratings (evaluations) and do not require active solicitation from the user. On the other hand, approaches based on probabilistic models, such as the matrix factorization model based on implicit trust, can be used to reduce tourist participation. Recent developments in this area include the use of hybrid systems combining approaches based on implicit trust with collaborative filtering methods of

explicit ratings taking into account the contextual information of each tourist.

In this article, we discussed in the second section, works that use explicit trust in the recommendation of items for users without a demographic profile. Then, we focused on implicit trust in the third section to show its advantage over the explicit declaration of trust relationships. These two trust inference methods can use the indirect relationships between users to improve the effectiveness of recommendations and alleviate the cold start problem due to data sparsity. For this reason, before concluding, we discussed the contribution of these two approaches to the field of tourism, highlighting their potential to use trust propagation to overcome limitations related to data sparsity and tourist reliability. Finally, this state-of-the-art review on the contribution of trust to item recommendation in general, and specific items in particular, allowed us to understand the advantages and limitations of existing approaches in order to propose new perspectives for item recommendation using AI.

## II. RECOMMENDER SYSTEMS BASED ON EXPLICIT TRUST

In this section, we will present a state-of-the-art review of works that rely on explicit trust declarations among users in order to classify them according to criteria such as the method used, the data set used, the performance metrics implemented evaluations and the adoption of the principle of trust propagation or not.

Golbeck and Hendler [1] established a website called FilmTrust, which integrates semantic web-based social networks with User Trust (UT) to generate movie recommendations. The ratings associated with this type of trust within this social network are used for calculating similarities within their own FilmTrust platform. Then, a comparison is made between the user's actual rating, the movie's average rating, and the rating suggested by the automatic collaborative filtering (ACF) algorithm. Finally, these predicted ratings are also compared with the nearest neighbor prediction algorithm, which is based on Pearson correlation.

In order to favor trust-based approaches over collaborative filtering (CF) techniques, Massa and Avesani [2] propose an algorithm that diffuses trust across a network to identify users that an active user can trust. This algorithm leverages explicit trust information provided by users of the Epinions.com site by allowing them to indicate the level of trust they attribute to each other. Then, this level of trust is related to how users perceive the relevance of reviews provided by specific users.

Finally, the evaluation of the predictions provided by the proposed algorithm is carried out using metrics such as mean absolute error (MAE), mean absolute error per user (MAUE), and user/rating coverage.

In this same context, Jamali and Ester [3] found that ratings provided by highly trusted friends for articles analogous to a targeted article are more reliable than all other ratings. For this reason, the authors implemented a random walk technique called TrustWalker to merge the recommendation strategies based on trust and on articles to avoid the impact of noisy data by considering a sufficient number of evaluations. Using this technique, the system calculates the trust in its predictions based on the Epinions dataset. To evaluate recommendation errors, the authors combined root mean square error (RMSE) and a coverage metric to calculate FMeasure to compare their approaches with the methods: TidalTrust, MoleTrust, CF Pearson and item-based models.

On the other hand, Jamali and Ester [4] implemented a model-based method named SocialMF designed to recommend content within social networks using matrix factorization techniques. These models incorporate trust propagation mechanisms and use matrix factorization to predict future user ratings. This method uses the Flixster and Epinions datasets and RMSE as the evaluation metric. To measure the effectiveness of this method, Jamali and Ester compare it to three models: the basic matrix factorization approach proposed in [5], user-based collaborative filtering (a memory-based approach) and the STE model from [6]. This comparison shows that the SocialMF method allows a significant reduction in recommendation errors (RMSE), especially in the case of new users.

Guo et al. [7] proposed a method called “Merge” aimed at explicitly integrating trusted neighbors identified by users into recommender systems to alleviate the cold start problem. In their experiments, these authors used three real-world datasets from FilmTrust, Flixster and Epinions to compare their proposed method with different approaches, including TrustAll, a collaborative filtering technique using the Pearson Correlation Coefficient (PCC) measure to calculate the similarity between users, the MoleTrust method [8]. The evaluation of the obtained results was carried out using performance measures of accuracy and coverage of notations such as mean absolute error (MAE). These results demonstrated that the Merge method does not require trust propagation.

TABLE I. RSS BASED ON EXPLICIT TRUST

Author	Method	Dataset	Evaluation metrics	Trust Propagation
FilmTrust Golbeck 2006 [1]	CF memory based	FilmTrust	MAE	Yes
MoleTrust Massa 2009 [2]	TARS <sup>1</sup>	Epinions	MAE MAUE Ratings coverage Users coverage	Yes
TrustWalker Jamali	CF memory	Epinions	RMSE Coverage	No

<sup>1</sup> Trust-Aware Recommender Systems

2009 [3]			FMeasure	
SocialMF Jamali 2010 [4]	CF Model based (MF)	Epinions Flixster	RMSE	Yes
Merge Guo 2012 [7]	TARS	FilmTrust Flixster Epinions	MAE Rating coverage	Yes

### III. RECOMMENDER SYSTEMS BASED ON IMPLICIT TRUST

In this section, we will present a state-of-the-art review of works that use implicit trust relationships between users in order to classify them according to criteria such as the method used, the data set used, the evaluation metrics implemented and the adoption of the principle of trust propagation or not.

Pitsilis and Marshall [9] use similarity measures between users according to the Pearson coefficient while integrating their trust relationships. Then, they calculate the predictions using the Resnick formula. This trust approach is asymmetric and requires the calculation of an initial prediction from a MovieLens dataset coming from a Collaborative Filtering system. Finally, to evaluate this approach, an average error percentage is calculated.

In the same context, O’Donovan and Smyth [10] propose a collaborative filtering approach aimed at improving the accuracy of recommendations. They suggest integrating trust mechanisms to refine the selection and weighting of recommendation partners in the recommendation process. They propose several trust calculation models based on past rating behaviors of individual profiles, encompassing both profile-level and item-level. In their experiment, they use the well-known MovieLens dataset and implement Resnick’s prediction methodology. To evaluate the accuracy of their trust-based prediction techniques after computing an initial prediction, they compare the average recommendation error of their approach with Resnick’s standard prediction method.

Papagelis et al. [11] present an approach to mitigate data sparsity using trust inferences. This approach uses the trust established between two users through Pearson Correlation based on ratings. Then, the system propagates this trust using transitive relationships between users within a social network where the experimental data comes from a movie SR called MRS. Finally, this work is evaluated using MAE and Receiver Operating Characteristic (ROC) sensitivity to compare it to collaborative filtering techniques that do not consider transitive associations.

In [12], the authors present an approach that argues that the accuracy of a user’s past predictions plays a crucial role in determining its reliability. This approach improves traditional recommendation techniques by integrating trust into the CF recommendation process. In their work, Hwang and Chen calculate an initial prediction using Resnick’s prediction formula and a trust score from user rating data. Then, they exploit the spread of trust in the trust network to infer indirect relationships and define these two key measures of trust: global trust and local trust. Then, they calculate the PCC and use the Resnick prediction formula for the final rating

predictions. Finally, they calculate the MAE and coverage to compare the recommendation accuracies of different trust configurations with those generated by the standard CF technique.

In [13], the authors proposed an algorithm called "trusted k-nearest recommenders" (kNR) which defines trust as the distance between the user's rating and the recommender's rating, increasing as the gap decreases. The highest level of trust is given to users who rated an item exactly as the user did. In their work, Lathia et al. used metrics such as MAE and root mean square error (RMSE) to compare the performance of their method against two similarity measures: the weighted-Pearson correlation coefficient and the proportion of co-rated items.

Lifen uses conventional similarity measures derived from Collaborative Filtering (CF) to establish potential trust between correlated entities. Trust is expressed as opinions, modeled using subjective logic. The formation of opinions relies on the availability of evidence. Therefore, the degree of trust between entities depends on the perceived similarity of their choices to enable transitivity of trust [14]. The author evaluates the effectiveness of his approach by using the "MovieLens" data set to calculate the divergence between the predicted rating generated by his method and the actual rating provided by the entity. This evaluation is performed by using the percentage of successful estimates obtained to compare the performance of his proposal against the average of all recommendations.

Yuan et al. [15] propose an implicit trust-aware recommendation system, iTARS, with the maximum trust propagation distance of iTARS, improving the conventional eTARS (explicit TARS) model by predicting ratings without explicit trust statements. They use similarities between users to generate implicit trust between users. Recommendations are weighted based on active users' implicit trusts in the recommenders to generate the predicted ratings. They define the implicit trust network as dynamic: a user can join at any time if it has a high similarity with other users and shares a certain number of rated items in common with an existing user of this implicit trust network. They use the Epinions dataset. They examined their proposed iTARS by comparing it to eTARS, based on rating prediction accuracy, rating prediction coverage, and computational complexity.

This paper [16] focuses on how e-governments can support businesses in the problem of selecting a reliable business partner to carry out reliable business transactions. In the process of selecting a business partner, trust or reputation information is crucial and has a significant influence on a business user's decision whether or not to do business with other business entities. Shambour and Lu propose a hybrid trust-enhanced CF recommendation approach (TeCF), which integrates the implicit trust filtering and user-based enhanced CF approaches. This study measures the trustworthiness of a given user based on their history of trusted recommendations. The MovieLens dataset is used to evaluate the performance of the proposed recommendation approach. They use different metrics to evaluate the quality of the recommendations produced, including Resnick's MAE and the coverage metric. They compare the recommendation performance of the proposed implicit trust filtering, enhanced user-based CF, and hybrid TeCF approaches with Resnick's user-based CF approach.

Bedi and Sharma [17] proposed a system that integrates a notion of dynamic trust between users by selecting a restricted and high-quality neighborhood based on the Ant Colony Optimization (ACO) algorithm to generate recommendations. They used data from both the Jester dataset and the MovieLens dataset. To evaluate the effectiveness of their proposed system, they implemented the traditional CF method by calculating the similarity between users using Pearson's correlation coefficient and predicting the ratings using of Resnick's prediction formula. Evaluation metrics such as precision, recall, and F1 measures were used to evaluate their TARS approach.

Shambour and Lu [18] proposed a recommendation system based on Collaborative Filtering that combines trust information and semantic data to address the problems of sparsity and cold start. They evaluate the trustworthiness of a user by measuring the accuracy of the predictions they made as a recommender for the active user by calculating initial predictions, using the mean square difference (MSD) method. The Jaccard measure is used as a weighting scheme to assess the relationship between common ratings and the set of all rated items, thereby calculating the derived implicit trust. Incorporating trust propagation makes it possible to infer trust and establish new ties among users who do not have direct trust ties. Using MovieLens and Yahoo! Webscope R4E like datasets, Shambour and Lu used metrics such as MAE and Coverage to compare their approach with benchmark algorithms like Resnick's user-based CF [19], Sarwar item-based CF [20], O'Donovan-Trust [10] and semantic filtering based on Ruiz-Semantic [21].

In this article, Zhang et al. [22] present a method to solve the sparsity problem by constructing a small-world implicit trust network. The construction of this small-world implicit trust network is based on the grouping of users (user clustering) and the implicit trust relationships between them. They choose the MovieLens 100K dataset as the experimental data. The performance of their proposed ARA algorithm is evaluated using MAE and F-measure metrics. To evaluate the effectiveness of the ARA algorithm, the authors perform a comparative analysis with the following algorithms: (1) CF, a classic user-based collaborative filtering algorithm; (2) O'Donovan, a collaborative filtering algorithm based on the item-level trust model proposed by O'Donovan; and (3) basic MF, a collaborative filtering algorithm based on basic matrix factorization.

In this paper, Shambour and Lu [23] present an effective recommendation approach called Hybrid User-Item Trust-based (HUIT), which integrates implicit trust information of users and items. A key aspect of their proposed approach is the inclusion of user and item reputations. The main goal of the HUIT approach is to improve the quality of recommendations by expanding the neighborhoods of active users and target items. This extension is achieved by integrating alternative information from historical assessments, seamlessly integrating implicit trust details as part of Collaborative Filtering.

To deal with data sparsity and Cold Start user problems, the HUIT approach leverages the intuitive features of implicit trust and trust propagation among users in the user-based implicit trust model, taking into account the reputation of users. The performance evaluation of the HUIT recommendation approach involves experiments conducted on three datasets: MovieLens, Yahoo! Webscope R4 and

FilmTrust. Evaluation metrics, including standard MAE and coverage metrics, are used for comprehensive analysis. The results of the HUIT recommendation approach are systematically compared with those of benchmark recommendation algorithms, including Resnick user-based CF [19], Sarwar item-based CF [20], O'Donovan user-based trust [10], and Kim item-based trust [24].

Roy et al. present a new similarity approach based on implicit trust between users [25]. This approach aims to improve the precision and reliability of predictions by considering similarity as asymmetric in the face of evolving user interests. These authors calculate user trust scores using the psychology forgetting curve, confidence, mean square difference (MSD), and trust between users to create a trust matrix. Finally, to evaluate their method, the authors used the MovieLens dataset and the MAE to measure the accuracy of the recommendations using their proposed method and they compared the quality of the recommendations obtained with those calculated by the different traditional trust-based approaches, such as TFS [18], JMSD [26], O'Donovan-Trust [10] and Resnick-UCF [19].

Zahir et al. [27] proposed an innovative trust-based method called AgreeRelTrust. This method does not require the initial prediction calculation because it merges the positive and negative agreements between users as well as their relative activities to obtain the trust relationship. To evaluate their method using datasets such as GroupLens and MovieLens, Zahir et al. used MAE and RMSE to measure the accuracy of their model's predictions. These measurements made it possible to compare the results of their method with the fundamental kNN approach and the O'Donovan trust-based method.

TABLE II. RSS BASED ON IMPLICIT TRUST

Author	Method	Dataset	Evaluation Metrics	Trust Propagation
Pitsilis 2004 [9]	CF	MovieLens	Mean Error Rate	No
O'donovan 2005 [10]	CF	MovieLens	Mean Error Rate	No
Papagelis 2005 [11]	CF	Movie RS "MRS"	MAE ROC	Yes
Hwang 2007 [12]	CF	MovieLens	MAE Coverage	Yes
Lathia 2008 [13]	CF	MovieLens	MAE RMSE Coverage	No
Lifen 2008 [14]	CF	MovieLens	divergence predicted /real rate	Yes
Yuan 2010 [15]	TARS	Epinions	MAE Coverage	Yes
Shambour 2011 [16]	User-based (CF)	MovieLens	MAE Coverage	Yes
Bedi 2012 [17]	TARS	Jester MovieLens	Precision Recall F-measure	No

Shambour 2012 [18]	CF User / item- based	MovieLens Yahoo! Webscope R4	MAE Coverage	Yes
Zhang 2014 [22]	CF	MovieLens	MAE F-measure	Yes
Shambour 2015 [23]	CF User and item- based	MovieLens Yahoo! Webscope R4 FilmTrust	MAE Coverage	Yes
Roy 2015 [25]	CF	MovieLens	MAE	Yes
Zahir 2019 [27]	Memory based CF	GroupLens MovieLens Jester	RMSE MAE	No

#### IV. ANALYSIS AND DISCUSSION

The two families of recommendation approaches cited above are based on the use of two types of trust (explicit and implicit) between users and use evaluation metrics such as mean absolute error (MAE), root mean square error (RMSE), and other metrics to estimate the performance of approaches.

The first family of trust approaches focuses on explicit declarations of trust between users and the diffusion of trust across a network while the second family of trust approaches emphasizes the use of implicit trust relationships between users and the propagation of these trust relationships.

In this article, several works on explicit trust between users are cited such as those of Golbeck and Hendler, Massa and Avesani, Jamali and Ester, Guo et al., etc. On the other hand, several works on implicit trust are mentioned such as the works of Pitsilis and Marshall, O'Donovan and Smyth, Papagelis et al., Hwang and Chen, Lathia et al., Yuan et al., Shambour and Lu, Bedi and Sharma, etc.

In the following, Table III compares explicit trust and implicit trust.

TABLE III. COMPARISON BETWEEN EXPLICIT AND IMPLICIT TRUST

Comparison criteria	Explicit trust	Implicit trust
Declaration of trust relationships	Yes	No
Using Direct Trust Propagation	Yes	Yes
Actual trust values (reliability)	Yes	No
Inferred (calculated) trust values	Yes	Yes
Evolution with user behavior	No	Yes
Addressing the problem of data sparsity relating to trust relationships	No	Yes
A considerable computational cost	No	Yes
Mitigating the cold start problem	No	Yes

In summary, this article places more emphasis on implicit trust relationships and the contribution of trust propagation compared to explicit trust declarations and their diffusions.

## V. CONCLUSION

In conclusion, this article explores the growing application of artificial intelligence (AI) in the field of smart tourism, highlighting the use of Implicit Trust-based Recommender Systems (ITRS) to improve the relevance of item recommendations for tourists. In this article, the focus is on ITRSs, which leverage implicit trust relationships among tourists, inferred from their past actions such as reviews, check-ins, and clicks. For this reason, the article contains two distinct sections. The first looks at work using explicit trust, while the second focuses on implicit trust. The analysis highlights the benefits of implicit trust as it reduces the need for active user participation and alleviates the cold start problem of data sparsity. In summary, this state-of-the-art provides a comprehensive understanding of the advantages and limitations of existing approaches, opening the way to new perspectives for item recommendation in the context of smart tourism using AI.

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